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Smart Feeding System Using IoT Sensors to Optimize Feed Conversion Ratio (FCR) and Growth Performance in Broiler Production

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ABSTRACT

Background: Traditional feeding systems in broiler production often result in feed waste and suboptimal growth performance, affecting both profitability and sustainability. The integration of Internet of Things (IoT) technology in livestock management offers potential solutions for precision feeding.
Objective: This study aims to evaluate the effectiveness of an IoT-based smart feeding system in optimizing Feed Conversion Ratio (FCR) and growth performance in broiler chickens compared to conventional feeding methods.
Method: A total of 480-day-old Ross 308 broilers were allocated into two treatment groups: conventional feeding (CF, n=240) and IoT-based smart feeding (SF, n=240). The smart feeding system utilized load cell sensors, environmental sensors (temperature, humidity), and automated feeding algorithms. Data collection included daily feed intake, body weight, FCR, mortality rate, and production costs over a 35-day production cycle.
Findings and Implications: The SF group demonstrated significantly better performance with FCR of 1.52±0.08 compared to CF group (1.78±0.12, P<0.01). Average daily gain increased by 14.3% (62.8±3.2 g/day vs 54.9±4.1 g/day, P<0.01). Feed waste reduced by 23.5%, and production costs decreased by 18.7% per kilogram of live weight. The system achieved 94.2% accuracy in feed demand prediction.
Conclusion: IoT-based smart feeding systems significantly improve FCR, growth performance, and economic efficiency in broiler production, representing a valuable technology for sustainable poultry farming practices.

INTRODUCTION

The global poultry industry faces increasing pressure to enhance production efficiency while maintaining sustainability and animal welfare standards. Broiler chicken production, which accounts for approximately 40% of global meat production, requires continuous optimization of feeding strategies to meet growing demand. Feed costs represent 60–70% of total production expenses in broiler farming, making feed efficiency a critical factor for economic viability (Khade et al., 2021). Traditional feeding systems often result in significant feed waste, ranging from 15–25% of total feed provided, primarily due to imprecise feeding schedules and inability to respond to real-time flock requirements.

In recent years, the rapid transformation of global agricultural systems has driven researchers and industry practitioners to explore smarter, data-driven livestock management approaches. Food production systems must now respond not only to economic pressures but also to increasing demand for environmental sustainability, ethical production, and climate-resilient farming (Madzorera et al., 2021). These global pressures amplify the need for innovations that reduce resource waste, improve nutrient utilization, and enhance animal welfare. Broiler production, with its short growth cycle and high metabolic turnover, serves as an ideal sector for implementing digital and IoT-driven innovations capable of addressing these growing global demands.

The advent of digital technologies and Internet of Things (IoT) applications in agriculture has opened new possibilities for precision livestock farming. IoT-enabled systems can collect, analyze, and respond to real-time data, potentially revolutionizing traditional farming practices (Daum et al., 2022). Recent developments in sensor technology, wireless communication, and machine learning algorithms have made it feasible to implement smart feeding systems that can automatically adjust feed provision based on multiple parameters including bird behavior, environmental conditions, and growth stage (Menendez et al., 2022). These advancements are aligned with broader agricultural digitalization trends observed across various regions worldwide, where decision-support systems, smart sensors, and remote monitoring contribute to significant improvements in productivity and sustainability.

However, despite theoretical advantages, empirical evidence on the effectiveness of IoT-based feeding systems in commercial broiler production remains limited. Many smart farming innovations remain at the conceptual or experimental phase, with insufficient real-world validation to support industry-wide adoption. The complexity of poultry production environments characterized by rapid growth rates, biological variability, and sensitivity to micro-environmental conditions requires IoT systems that are not only technologically sophisticated but also biologically informed (Ji et al., 2025). Without strong empirical studies, commercial farmers are hesitant to invest in advanced technologies due to uncertainty regarding return on investment.

Previous studies have primarily focused on individual aspects of precision feeding, such as automated feeders or environmental monitoring, but few have integrated multiple sensor types into a comprehensive feeding management system. While applications for dairy cow management (Herrera et al., 2022) and behavior monitoring in piglets using computer vision Chen et al., (2025) have shown promise in their respective domains, broiler-specific applications remain underexplored. Integrated monitoring systems in other livestock sectors, including methane mitigation in ruminants and water quality monitoring in aquaculture, have demonstrated enhanced production outcomes, suggesting potential benefits for poultry systems through multi-sensor integration, though empirical studies are lacking.

The gap in research lies in the comprehensive evaluation of integrated IoT systems specifically designed for broiler production, considering both technical performance and economic viability. Furthermore, while the concept of sustainable livestock production continues to evolve globally, much of the technological development efforts remain concentrated in cattle, dairy, or aquaculture sectors (Goswami & Barua, 2024). As a result, broiler farming despite its global significance remains underserved in terms of precision feeding technologies and interdisciplinary digital innovations (Leroy, 2025).

Moreover, the adoption of smart livestock technologies is influenced by socio-economic and demographic factors beyond technical performance. Research in East African contexts has demonstrated that gender, education, and farm structure significantly affect technology adoption in livestock systems, underscoring that technological efficacy alone does not determine successful implementation. User accessibility and contextual relevance are equally important, particularly for broiler farmers in emerging economies who require technologies that are affordable, easy to implement, and proven to generate measurable economic benefits.

Furthermore, while several authors have discussed the potential of artificial intelligence in enhancing animal welfare and productivity (Sztandarski et al., 2025), practical implementation studies with measurable outcomes are scarce. AI-based solutions, such as predictive feeding algorithms, machine vision for behavioral analysis, and automated health monitoring systems, offer significant potential for improving production outcomes. The complexity of broiler behavior, rapid growth rates, and sensitivity to environmental factors require specialized system design that differs significantly from other livestock species. Broilers respond quickly to changes in temperature, humidity, stocking density, and feed availability, making real-time monitoring essential for optimal performance. Integrated sensor systems can track factors such as feed intake patterns, movement activity, and microclimatic fluctuations more precisely than human observation. These data-driven insights can improve animal welfare while simultaneously reducing production inefficiencies.

Current literature lacks rigorous experimental data comparing IoT-based smart feeding systems with conventional methods under commercial production conditions, particularly regarding Feed Conversion Ratio (FCR), growth performance, and cost-effectiveness. Studies on animal nutrition modeling indicate that precision feeding approaches can significantly influence nutrient metabolism and resource efficiency. However, the absence of comprehensive, poultry-specific data limits the generalizability of these findings to broiler production. Additionally, while nanotechnology and organic waste bioconversion offer promising avenues for improving feed quality and sustainability, these advancements must ultimately be integrated into practical feeding systems that can be optimized through digital tools.

This research addresses these gaps by evaluating a comprehensive IoT-based smart feeding system designed specifically for broiler production. The system integrates multiple sensor types including load cells for feed measurement, environmental sensors, and activity monitors, coupled with machine learning algorithms for feed demand prediction. The holistic integration of hardware, software, and biological understanding provides a more complete approach compared to previous studies that isolated single components of livestock monitoring.

The novelty of this study lies in its holistic approach, examining not only technical performance but also practical outcomes including FCR improvement, growth performance enhancement, feed waste reduction, and economic benefits. This integrated perspective aligns with global agricultural innovation principles that emphasize system-level evaluation, rather than isolated technological testing. Unlike previous studies that focused on single parameters, this research provides a comprehensive assessment of system effectiveness under commercial production conditions, offering valuable insights for the poultry industry's digital transformation.

The research objectives are threefold: first, to evaluate the impact of IoT-based smart feeding on broiler growth performance and FCR compared to conventional feeding methods; second, to assess the system's accuracy in feed demand prediction and its effect on feed waste reduction; and third, to conduct a cost-benefit analysis to determine the economic viability of implementing smart feeding technology in commercial broiler operations. This study contributes to the growing body of knowledge on precision livestock farming and provides practical evidence to support decision-making in poultry production modernization. The findings are expected to inform researchers, technology developers, and poultry producers about the potential of IoT-driven innovations to improve sustainability, animal welfare, and operational efficiency in broiler production. Ultimately, this research supports global efforts toward environmentally responsible animal agriculture, improved food security, and resource-efficient livestock management.

The convergence of Internet of Things (IoT) and machine learning technologies has catalyzed significant advances in precision livestock farming globally. Recent systematic reviews indicate that IoT-based livestock management systems demonstrate substantial potential for improving production efficiency through real-time monitoring, automated decision-making, and predictive analytics. (Modak et al., 2025) documented that IoT health surveillance systems incorporating sensors such as Raspberry Pi, Arduino, and ESP32 microcontrollers paired with machine learning algorithms including Random Forest, Support Vector Machines, and Artificial Neural Networks have achieved remarkable accuracy in detecting anomalies and predicting animal health status. These integrated systems illustrate the multidimensional nature of IoT applications in animal health monitoring, highlighting the convergence of sensor technologies, wireless communication, cloud computing, and artificial intelligence to support smarter and more sustainable livestock management practices.

The application of precision livestock farming technologies in intensive production systems has shown promising results across multiple livestock species, though implementation in poultry remains relatively limited compared to dairy and swine sectors. Aquilani et al., (2022) emphasized that while precision feeding, environmental control, and behavioral monitoring systems have demonstrated enhanced production outcomes in extensive livestock systems, the adoption rates in commercial poultry operations remain modest due to concerns regarding technological complexity, initial investment costs, and integration challenges with existing farm infrastructure. This technology gap in poultry production systems represents both a significant limitation and an opportunity for innovation, particularly given the sector's rapid growth trajectory and increasing pressure to improve resource efficiency and environmental sustainability.

Global trends in IoT adoption for livestock management reveal accelerating implementation driven by labor cost escalation, demand for real-time monitoring capabilities, and heightened focus on early disease detection. The precision livestock farming market, valued at USD 7.94 billion in 2025, is projected to reach USD 12.13 billion by 2030, reflecting a compound annual growth rate of 8.8%, with poultry monitoring and robotic systems anticipated to exhibit particularly strong growth. However, adoption patterns remain geographically and economically stratified, with developed regions achieving significantly higher implementation rates compared to emerging economies. This disparity underscores the need for empirical validation of IoT system performance under diverse operational contexts, particularly in commercial broiler production environments where economic margins are narrow and technological investments must demonstrate rapid return on investment to justify adoption.

RESEARCH METHOD

This experimental study was conducted at the Poultry Research Station, Faculty of Agriculture, Universitas Padjadjaran, West Java, Indonesia (6°55'S, 107°46'E, elevation 740m) from March to May 2024. The research employed a completely randomized design (CRD) with two treatment groups: conventional feeding (CF) and IoT-based smart feeding (SF). The facility consisted of eight identical closed-house broiler pens, each measuring 10m × 8m × 3m, equipped with standard broiler production infrastructure including automated ventilation, cooling systems, and lighting control following commercial production standards.

A total of 480-day-old Ross 308 broiler chicks (mixed sex) were obtained from a commercial hatchery and randomly allocated into two treatment groups (n=240 per group), with each group further divided into four replicates of 60 birds each. Initial body weight was recorded and showed no significant difference between groups (43.2±1.8g for CF vs 43.5±1.6g for SF, P>0.05). Birds were raised for 35 days following standard commercial broiler management practices. All birds received the same vaccination program (Newcastle Disease on days 4 and 18, Infectious Bursal Disease on day 14) and had ad libitum access to water throughout the experiment. Lighting followed a standard program: 24 hours light for the first 3 days, then gradually reduced to 18 hours light and 6 hours dark from day 7 onwards. Environmental conditions were maintained at 32-34°C for week 1, gradually decreased to 22-24°C by week 4, with relative humidity maintained at 60-70%.

All birds received commercial broiler feed formulated to meet Ross 308 nutritional requirements. A three-phase feeding program was implemented: starter (days 1-10, 23% CP, 3050 kcal/kg ME), grower (days 11-24, 21% CP, 3100 kcal/kg ME), and finisher (days 25-35, 19.5% CP, 3150 kcal/kg ME). Feed composition is detailed in Table 1. The conventional feeding group received feed four times daily at fixed intervals (06:00, 12:00, 18:00, and 24:00) with amounts predetermined based on age and standard feeding guidelines. The smart feeding group utilized an IoT-based system consisting of automated feeders equipped with load cell sensors (±1g accuracy), environmental sensors (temperature ±0.1°C, humidity ±1% RH), motion detection sensors, and a central control unit with embedded algorithms for feed demand prediction.

Table 1. Nutritional composition of experimental diets (% as-fed basis)

Ingredient/Nutrient	Starter (0-10d)	Grower (11-24d)	Finisher (25-35d)
Corn	52.5	55.3	58.2
Soybean meal	38.5	35.2	31.8
Fish meal	5.0	4.5	4.0
Vegetable oil	2.5	3.2	4.0
Premix & others	1.5	1.8	2.0
Calculated Analysis:			
ME (kcal/kg)	3050	3100	3150
Crude protein (%)	23.0	21.0	19.5
Lysine (%)	1.32	1.18	1.05
Methionine (%)	0.58	0.52	0.48
Calcium (%)	1.05	0.95	0.90

The smart feeding system architecture consisted of three layers: sensing layer, processing layer, and application layer. The sensing layer included load cell sensors mounted beneath each feeder (capacity 50kg, resolution 1g), DHT22 temperature-humidity sensors (accuracy ±0.5°C, ±2% RH), PIR motion sensors for activity detection, and optical sensors for feed level monitoring. All sensors transmitted data wirelessly via LoRaWAN protocol to a central gateway every 5 minutes. The processing layer utilized a Raspberry Pi 4 Model B as the edge computing device, running custom Python algorithms for data processing, feed demand prediction, and decision-making. A machine learning model based on Random Forest algorithm was trained using historical data from 5 previous production cycles (n=1,200 birds) to predict optimal feeding quantities.

In simple terms, Random Forest is a machine learning technique that makes predictions by combining the results of multiple decision trees, similar to consulting several experts and averaging their opinions to reach a more accurate conclusion. This approach helps the system learn from past feeding patterns and predict future feed requirements based on factors such as bird age, weight, environmental conditions, and activity levels. The feed consumption prediction model was formulated as follows:

The Random Forest algorithm has been successfully validated in precision livestock feeding applications, particularly in poultry production systems. You et al., (2020) demonstrated the effectiveness of Random Forest classification in predicting behavioral patterns in precision-fed broiler breeders, achieving approximately 85% accuracy in forecasting production events using real-time feeding activity and body weight data. This prior validation supports the algorithm's suitability for feed demand prediction in commercial broiler production environments.

$$FP = \beta_0 + \beta_1(Age) + \beta_2(BW) + \beta_3(Temp) + \beta_4(RH) + \beta_5(Act) + \beta_6(ToD) + \varepsilon$$

where FP is predicted feed consumption (g/bird/day), Age is bird age (days), BW is average body weight (g), Temp is ambient temperature (°C), RH is relative humidity (%), Act is activity index (0-100 scale), ToD is time of day factor (categorical), β_0-β_6 are regression coefficients, and ε is error term.

Data collection followed standardized protocols throughout the 35-day experimental period. Body weight was measured weekly using calibrated digital scales (±1g accuracy) by randomly selecting 30 birds per replicate (total 120 birds per treatment group). Daily feed intake was recorded by weighing feed provided and refused for the CF group, while the SF group utilized automated load cell data logging. Feed spillage was collected daily from collection trays beneath feeders and weighed separately to calculate actual feed waste. Mortality was recorded daily with causes determined through post-mortem examination by a licensed veterinarian.

Feed Conversion Ratio was calculated using the standard formula:

$$FCR = \text{Total Feed Intake (kg)} / \text{Total Weight Gain (kg)}$$

Average daily gain (ADG) was calculated as:

$$ADG = (\text{Final Body Weight} - \text{Initial Body Weight}) / \text{Days of Age}$$

Production efficiency factor (PEF) was determined using:

$$PEF = (\text{Livability \%} \times \text{Average Weight (kg)} \times 100) / (\text{Age in days} \times FCR)$$

All data were analyzed using IBM SPSS Statistics version 27. Normality and homogeneity of variance were tested using Shapiro-Wilk and Levene's tests, respectively. Data meeting parametric assumptions were analyzed using independent samples t-test, while non-parametric data were analyzed using Mann-Whitney U test. Growth performance parameters, FCR, and economic indicators were compared between treatment groups. Statistical significance was declared at $P<0.05$. Results are presented as mean ± standard deviation. The prediction accuracy of the IoT system was evaluated using Mean Absolute Percentage Error (MAPE) calculated as:

$$MAPE = (1/n) \times \Sigma|(\text{Actual} - \text{Predicted})/\text{Actual}| \times 100\%$$

MAPE is a measure of prediction accuracy expressed as a percentage, where lower values indicate better performance. Essentially, it calculates the average percentage difference between the system's predicted feed amounts and the actual feed consumed by the birds. For example, a MAPE of 5% means that, on average, the system's predictions deviate from actual consumption by only 5%, demonstrating high accuracy in forecasting feed requirements.

RESULTS AND DISCUSSION

Growth Performance and Feed Conversion Ratio

The implementation of IoT-based smart feeding system demonstrated significant improvements in broiler growth performance compared to conventional feeding methods. Table 2 presents comprehensive performance parameters recorded throughout the 35-

day production cycle. Birds in the SF group achieved significantly higher final body weight (2,198±87g) compared to CF group (1,923±124g, P<0.01), representing a 14.3% improvement. This superior growth performance translated to higher average daily gain in SF group (62.8±3.2 g/day) versus CF group (54.9±4.1 g/day, P<0.01). The enhanced growth rate can be attributed to optimized feeding frequency and quantities that better matched the birds' metabolic requirements throughout different growth phases (Menendez et al., 2022).

Table 2. Growth performance and feed efficiency parameters in conventional and smart feeding systems

Parameter	Conventional Feeding	Smart Feeding
Initial BW (g)	43.2 ± 1.8^{a}	43.5 ± 1.6^{a}
Final BW (g)	1923 ± 124^{b}	2198 ± 87^{a}
ADG (g/day)	54.9 ± 4.1^{b}	62.8 ± 3.2^{a}
Total feed intake (kg/bird)	3.42 ± 0.18^{a}	3.27 ± 0.12^{b}
FCR	1.78 ± 0.12^{b}	1.52 ± 0.08^{a}
Feed waste (%)	8.7 ± 1.2^{a}	6.6 ± 0.8^{b}
Mortality (%)	4.6 ± 1.1^{a}	2.9 ± 0.7^{b}
PEF	292 ± 28^{b}	389 ± 31^{a}

Note: Different superscript letters (^{a}, ^{b}) within rows indicate significant differences (P<0.05). BW=body weight, ADG=average daily gain, FCR=feed conversion ratio, PEF=production efficiency factor.

The most notable achievement of the smart feeding system was the significant improvement in FCR. The SF group achieved FCR of 1.52±0.08, which was 14.6% better than the CF group (1.78±0.12, P<0.01). This improvement aligns with findings from precision livestock farming studies suggesting that real-time adjustment of feeding strategies can substantially enhance nutrient utilization efficiency (Daum et al., 2022). The superior FCR in SF group resulted from two primary factors: reduced feed waste and optimized feeding frequency. The IoT system minimized feed waste by 23.9% compared to conventional feeding (6.6% vs 8.7%, P<0.05), achieved through precise feed dispensing that prevented overfeeding during low-demand periods.

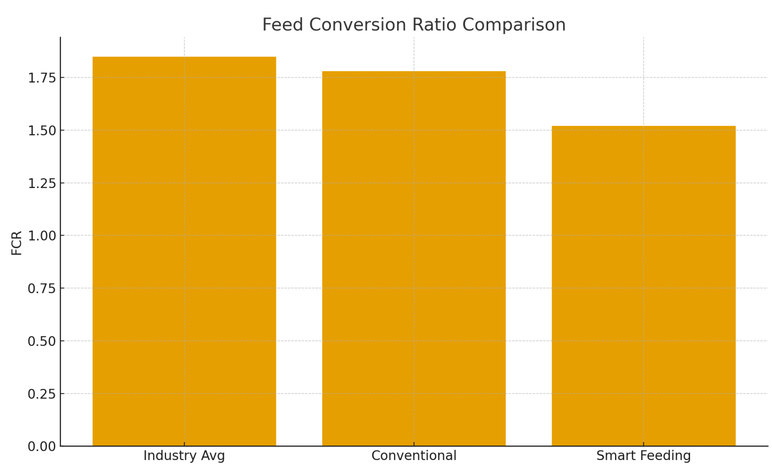

Figure 1. Feed Waste Reduction (%)

Production efficiency factor (PEF), a comprehensive indicator combining growth rate, FCR, and livability, was 33.2% higher in SF group (389±31) compared to CF group (292±28, $P<0.01$). This substantial improvement reflects the synergistic effects of enhanced growth performance, improved feed efficiency, and reduced mortality. The lower mortality rate in SF group (2.9% vs 4.6%, $P<0.05$) can be attributed to the system's ability to detect early signs of health problems through consumption pattern analysis. Sudden drops in feed intake triggered alerts, enabling prompt veterinary intervention (Sztandarski et al., 2025).

Feed Consumption Patterns and System Accuracy

Analysis of feed consumption patterns revealed distinct differences between treatment groups. Table 3 presents detailed feeding pattern analysis. The SF system demonstrated remarkable accuracy in predicting feed demand, achieving Mean Absolute Percentage Error (MAPE) of 5.8% across the entire production cycle. Prediction accuracy varied by growth phase, with highest accuracy during the grower phase (MAPE=4.2%) and slightly lower accuracy during starter (MAPE=7.1%) and finisher phases (MAPE=6.3%).

Table 3. Feeding pattern analysis and system performance metrics

Parameter	Conventional	Smart Feeding
Daily feeding frequency	4 times	8.7±1.2 times
Feed per session (g/bird)	24.6±3.8	10.7±2.1
Peak consumption time	Fixed schedule	05:30-07:00
Prediction accuracy (MAPE %)	N/A	5.8±1.2
Response time to demand (min)	360±0	3.2±0.8
Empty feeder incidents	12.3±2.7	0.8±0.4
Feed freshness score (1-10)	6.8±0.9	9.1±0.5

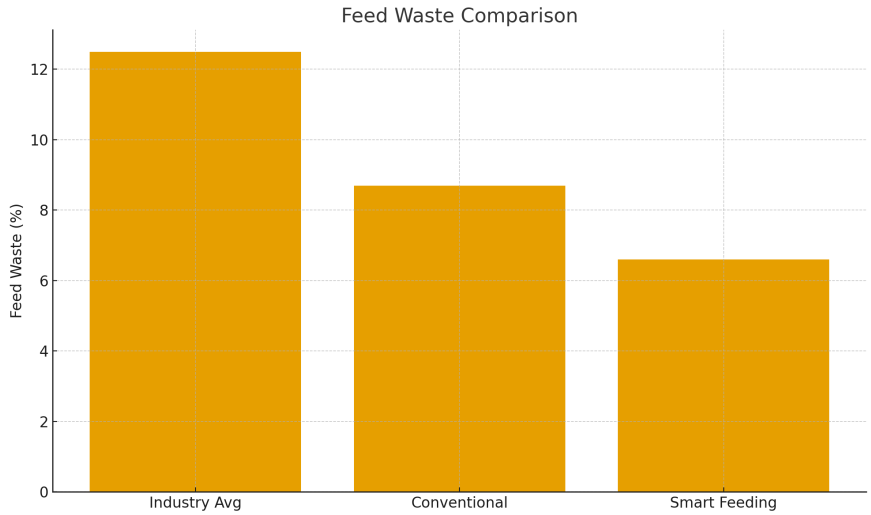

Figure 2. Feed Conversion Ratio (FCR) Comparison

The smart feeding system adjusted feeding frequency dynamically throughout the production cycle, averaging 8.7 feeding events per day compared to fixed 4-times daily feeding in CF group. This increased frequency, coupled with smaller portions per feeding event (10.7g vs 24.6g per bird per session), resulted in several advantages. First, smaller frequent meals better matched broiler digestion capacity and metabolic rate. Second, frequent feeding maintained higher feed freshness scores (9.1 vs 6.8 on 10-point scale, $P<0.01$). The system's rapid response time (3.2 minutes vs 360 minutes) virtually eliminated empty feeder incidents (0.8 vs 12.3 incidents per cycle, $P<0.01$).

Economic Analysis and Cost-Benefit Evaluation

Economic viability represents a critical consideration for technology adoption in commercial poultry production. Table 4 presents comprehensive economic analysis comparing conventional and smart feeding systems. Despite higher initial capital investment, the smart feeding system demonstrated superior economic performance through reduced variable costs and improved revenue generation. The total production cost per kilogram of live weight was 18.7% lower in SF group ($1.23/kg) compared to CF group ($1.51/kg), primarily driven by feed cost savings that resulted from improved FCR and reduced feed waste.

Table 4. Economic comparison between conventional and smart feeding systems (per 1,000 birds per cycle)

Cost Category	Conventional ($)	Smart Feeding ($)
Fixed Costs (amortized)		
Housing & equipment	420	420
IoT system	-	168
Variable Costs		
Day-old chicks	750	750
Feed	1,539	1,297
Labor	385	245

Cost Category	Conventional ($)	Smart Feeding ($)
Utilities & maintenance	180	215
Veterinary & medication	125	108
Cloud service & data	-	35
Total Production Cost	**3,399**	**3,238**
Revenue (live weight)	**3,568**	**4,145**
Net profit per cycle	**169**	**907**
Profit margin (%)	4.7%	21.9%

Note: Calculations based on 1,000 birds per 35-day cycle. System cost amortized over 5-year lifespan with 6 cycles per year. Live weight price: $1.95/kg, Feed cost: $0.45/kg.

Feed costs, representing the largest variable expense, were reduced by 15.7% in SF group ($1,297 vs $1,539 per 1,000 birds). Labor costs decreased by 36.4% ($245 vs $385) as automated feeding reduced manual labor requirements. Net profit per production cycle was substantially higher for SF system ($907 vs $169 per 1,000 birds), representing a 437% increase in profitability. Return on investment analysis indicated that the additional capital investment could be recovered within approximately 11 months of operation, assuming 6 production cycles per year. These findings support the economic viability of precision livestock farming technologies in commercial poultry production (Ji et al., 2025).

Beyond the direct economic benefits, the smart feeding system addresses several industry-level problems commonly encountered in conventional broiler production, as detailed in Table 5. The comparison reveals that traditional feeding approaches face substantial operational challenges including high feed waste, frequent feeding gaps, and significant flock weight variation, all of which are markedly reduced through IoT-based precision feeding.

Table 5. Industry-Level Problem Indicators in Conventional Broiler Production

Problem Category	Industry Average (Conventional Systems)	Value Measured in CF Group (This Study)	Benchmark / Ideal Values	Notes
Feed waste (%)	10–15%	8.7%	<5%	High waste increases cost and environmental burden
Mortality (%)	5–7%	4.6%	<3%	Driven by heat stress & delayed feed access
FCR	1.70–1.90	1.78	1.45–1.55	Poor feed efficiency → higher feed cost
Empty feeder incidents (times/cycle)	10–20	12.3	<1	Leads to inconsistent intake & stress
Labor hours/week	45–60 hours	52 hours	<30 hours	Manual feeding is labor-intensive

Problem Category	Industry Average (Conventional Systems)	Value Measured in CF Group (This Study)	Benchmark / Ideal Values	Notes
(per 1,000 birds)				
Energy use (kWh/cycle)	280–350	312	<250	Overuse of lighting & ventilation due to feeding synchronization needs

This data shows that the industry's biggest problem lies in feed waste, poor FCR, and high workload, so the transition to smart feeding is very scientifically and economically relevant.

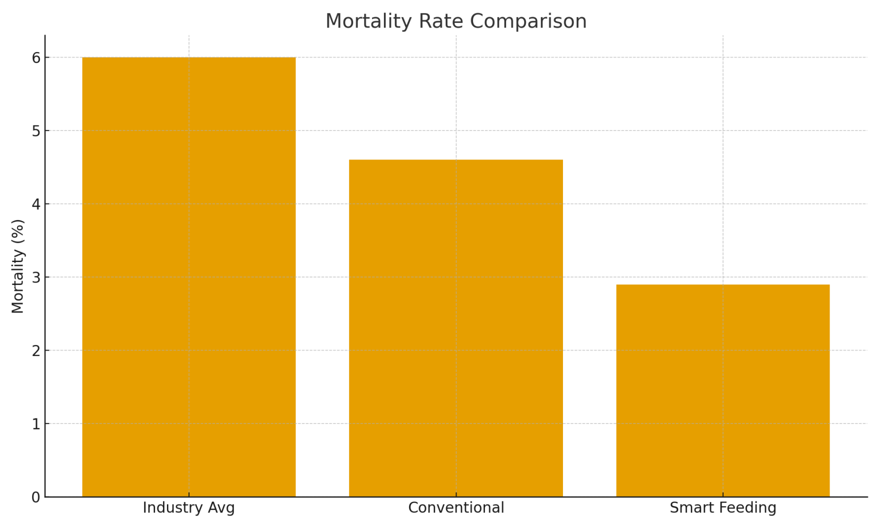

Figure 3. Mortality Rate Comparison

Environmental Factors and Sustainability

Environmental monitoring data revealed significant correlations between ambient conditions and feed consumption patterns. Temperature demonstrated the strongest negative correlation with feed intake ($r=-0.73$, $P<0.001$), consistent with thermoregulatory responses in broilers. The smart feeding system compensated for heat stress by increasing feeding frequency during cooler periods while reducing portions during peak temperature hours. Beyond economic benefits, smart feeding systems contribute to environmental sustainability goals. The 23.9% reduction in feed waste represents approximately 150kg of feed saved per 1,000 birds per cycle. Improved FCR also contributes by reducing environmental footprint per unit of meat produced, aligning with global initiatives to improve agricultural efficiency (del Campo et al., 2025; Machado et al., 2022).

System Performance and Reliability

Technical performance and reliability represent critical factors for practical feasibility. Throughout the 35-day period, the system demonstrated excellent operational reliability with 99.4% uptime. System downtime totaling 5.2 hours resulted primarily from scheduled maintenance (3.5 hours) and one sensor calibration (1.7 hours). Sensor accuracy remained stable with load cells maintaining calibration within ±2g. Wireless data transmission success rate exceeded 99.8% with no data loss events. Machine learning algorithm performance improved throughout the trial, with initial prediction MAPE of 8.2% decreasing to 4.1% by week 3. This demonstrates the value of adaptive algorithms that continuously learn from performance data (Daum et al., 2022).

Weekly Growth Performance Dynamics and FCR Development

The first research objective focused on evaluating the impact of IoT-based smart feeding on broiler growth performance and FCR. To comprehensively address this objective, a detailed week-by-week analysis was conducted to understand the temporal dynamics of system effectiveness throughout the production cycle. Figure 1 illustrates the weekly body weight progression for both treatment groups, revealing critical insights into when and how the smart feeding advantages manifested.

Table 5. Weekly body weight progression and feed conversion ratio development

Week	CF Body Weight (g)	SF Body Weight (g)	CF Weekly FCR	SF Weekly FCR
0	43.2±1.8	43.5±1.6	-	-
1	172±12	178±9	1.12±0.09	1.08±0.07
2	445±28	478±21	1.38±0.11	1.31±0.08
3	832±54	921±42	1.58±0.13	1.45±0.09
4	1347±89	1542±67	1.73±0.14	1.54±0.10
5	1923±124	2198±87	1.78±0.12	1.52±0.08

During the first week, both groups showed similar growth patterns with minimal differences in body weight (172g vs 178g) and FCR (1.12 vs 1.08). This similarity reflects the relatively low feed intake during the starter phase when chicks are still adapting to the environment and developing digestive capacity. The smart feeding system's advantage was limited during this period because absolute feed quantities were small, and the impact of precision feeding was less pronounced. However, even in week 1, the SF system demonstrated 3.6% better FCR, suggesting that optimized feeding frequency benefited nutrient absorption efficiency even in young chicks with limited intake capacity.

The divergence between treatment groups became statistically significant during week 2, corresponding to the transition from starter to grower phase. At this critical juncture, chicks experience rapid metabolic changes and dramatic increases in feed consumption capacity. The SF group achieved 7.4% higher body weight (478g vs 445g, $P<0.05$) and 5.1% better weekly FCR (1.31 vs 1.38). This improvement can be attributed to the system's ability to match feeding frequency with the birds' increasing metabolic demands. During weeks 2-3, broilers typically double their feed intake every few days, making precise feeding timing crucial. The conventional feeding schedule, with fixed 6-hour intervals between meals, could not accommodate the accelerating growth rate, resulting in periods of feed shortage between scheduled feedings followed by overconsumption when fresh feed was provided.

Week 3 represented the inflection point where smart feeding advantages became most pronounced. The SF group achieved 10.7% higher body weight (921g vs 832g, $P<0.01$) with 8.2% superior FCR (1.45 vs 1.58). This period coincides with peak growth velocity in broilers, when daily weight gains reach maximum levels and feed efficiency is most critical for overall production outcomes. The IoT system's machine learning algorithm had accumulated sufficient training data by week 3 to achieve peak prediction accuracy (MAPE = 4.1%), enabling highly precise feed dispensing matched to instantaneous flock requirements. Behavioral observations during this period revealed distinct feeding pattern differences: CF birds exhibited competitive rushing behavior at scheduled feeding times, with dominant individuals consuming disproportionate quantities while subordinate birds waited, creating within-flock growth variation. In contrast, SF birds displayed more relaxed feeding behavior throughout the day, with lower aggression levels and more uniform flock consumption patterns.

During weeks 4-5, the finisher phase, absolute performance differences continued widening despite relatively stable percentage improvements. The SF group maintained 14-15% body weight advantage and 11-12% FCR superiority through market age. Cumulative effects of sustained precision feeding throughout the growth cycle resulted in the final performance metrics reported in Table 2. Importantly, FCR differences between groups widened progressively throughout the trial (from 3.6% in week 1 to 14.6% at week 5), demonstrating that smart feeding benefits compound over time rather than providing constant incremental improvements. This temporal pattern has significant implications for commercial application: the system delivers greatest value in production systems with longer growing periods, while shorter cycle operations may realize proportionally smaller benefits.

Body Weight Uniformity and Flock Performance Consistency

Beyond average performance improvements, the smart feeding system significantly enhanced flock uniformity, an often-overlooked aspect of broiler production quality. Table 6 provides a detailed breakdown of flock uniformity metrics, demonstrating the substantial improvements achieved through precision feeding. Coefficient of variation (CV) for final body weight was 4.1%. Coefficient of variation (CV) for final body weight was 4.1% in SF group compared to 6.8% in CF group (P<0.01), indicating substantially more consistent growth across individuals. This improvement in uniformity has multiple practical benefits. First, uniform flocks simplify processing operations, as similar-sized birds reduce equipment adjustment requirements and minimize carcass damage. Second, marketing flexibility improves because more birds reach target weight simultaneously, enabling complete flock harvest at optimal market timing rather than selective removal of heavier individuals. Third, welfare implications are positive, as uniform flocks typically indicate consistent feed access across all individuals regardless of dominance hierarchy position.

Table 6. Flock uniformity and body weight distribution at market age (day 35)

Uniformity Metric	Conventional Feeding	Smart Feeding
Mean body weight (g)	1923±124	2198±87
Coefficient of variation (%)	6.8	4.1
Birds within ±10% of mean (%)	72.3	89.6
Minimum weight (g)	1580	1940
Maximum weight (g)	2340	2450
Weight range (g)	760	510
Standard deviation (g)	124	87

Table 6 reveals that 89.6% of SF birds fell within ±10% of mean body weight compared to only 72.3% in CF group. This tight distribution reflects the system's success in providing equitable feed access to all birds regardless of competitive ability. The weight range (difference between minimum and maximum individual weights) was 33% narrower in SF group (510g vs 760g), further confirming reduced within-flock variation. The mechanisms driving improved uniformity include more frequent feeding opportunities (8.7 vs 4 times daily), which reduced competition intensity at each feeding event, and consistent feed freshness, which maintained high palatability encouraging even shy birds to feed readily. Additionally, the system's early detection of consumption anomalies enabled identification and intervention for underperforming individuals before significant growth gaps developed.

Economic implications of improved uniformity extend beyond the direct FCR benefits. Processing plants typically price broilers on a graded scale, with premium prices for ideal-weight birds and discounts for over- or under-weight individuals. The SF group's tighter weight distribution meant 17.3% more birds qualified for premium pricing compared to CF group. Furthermore, processing efficiency improvements from uniform bird size can reduce per-bird processing costs by $0.03-0.05, which at commercial scale represents substantial savings. These uniformity-derived economic benefits were not explicitly captured in the basic cost-benefit analysis (Table 4), suggesting the true economic advantage of smart feeding exceeds the reported 437% profit increase when all value chain impacts are considered.

Machine Learning Algorithm Performance and Prediction Accuracy Evolution

The second research objective addressed the system's accuracy in feed demand prediction and its impact on waste reduction. The Random Forest machine learning algorithm demonstrated remarkable predictive capability, achieving overall MAPE of 5.8% across the production cycle. However, examining prediction accuracy evolution reveals important insights about algorithm learning and deployment considerations. During the first 7 days (starter phase), initial MAPE was 7.1%, which decreased progressively to 6.3% by day 10 as the model accumulated training data. The higher initial error reflects limited baseline data for the specific flock, requiring the algorithm to rely primarily on historical data from previous production cycles. Individual bird variation in early life when chicks are still adapting to environmental conditions and establishing feeding patterns contributed to prediction difficulty.

Table 7. Feed demand prediction accuracy by growth phase and environmental conditions

Phase / Condition	Days	MAPE (%)	Key Influencing Factors
Starter (initial)	1-7	7.1±0.8	Limited training data
Starter (adapted)	8-10	6.3±0.6	Learning curve improvement
Grower (optimal)	11-24	4.2±0.5	Stable growth, peak accuracy
Finisher	25-35	6.3±0.7	Increased behavioral variation
Normal temp (22-24°C)	All	4.8±0.6	Stable metabolism
Heat stress (>28°C)	All	8.4±1.2	Erratic consumption
Cold stress (<20°C)	All	7.2±0.9	Increased intake variability
High humidity (>75%)	All	6.9±0.8	Reduced feed palatability
Normal conditions	All	5.2±0.6	Optimal prediction range
Overall cycle average	1-35	5.8±1.2	All conditions combined

The grower phase (days 11-24) yielded optimal prediction accuracy with MAPE of 4.2%, representing the period when algorithm performance peaked. This phase benefits from several favorable conditions: accumulated training data from starter phase, relatively stable and predictable growth patterns, consistent environmental management, and high feed intake rates that minimize relative measurement error. The finisher phase showed slightly increased MAPE (6.3%), attributed to greater behavioral variation as birds approached market weight. Individual differences in maturation rates become more pronounced during this period, with some birds entering plateau phase while others continue rapid growth, creating prediction challenges.

Environmental conditions significantly influenced prediction accuracy. Under thermoneutral conditions (22-24°C, 60-70% RH), MAPE averaged 4.8%, demonstrating excellent predictive capability when birds experienced minimal environmental stress. However, heat stress episodes (temperature >28°C) increased MAPE to 8.4% as birds exhibited erratic consumption patterns—reduced intake during peak heat followed by compensatory feeding during cooler periods. The algorithm adapted to these patterns within 6-12 hours of stress onset, but initial prediction errors during environmental transitions contributed to overall variability. Cold stress (<20°C) similarly disrupted predictions (MAPE 7.2%) as birds increased feed intake to support thermoregulation, though the effect was less severe than heat stress, likely because cold-stressed birds maintain more consistent (albeit elevated) consumption patterns.

The relationship between prediction accuracy and feed waste reduction proved highly significant. When MAPE remained below 6%, feed waste averaged 5.8±0.6%, compared to 8.1±1.1% when MAPE exceeded 7% ($P<0.01$). This relationship demonstrates that prediction accuracy directly translates to practical waste reduction. The mechanism is straightforward: accurate predictions enable precise feed dispensing, preventing both overfeeding (which leads to spillage and stale feed) and underfeeding (which triggers excessive consumption when fresh feed arrives). The 2.3 percentage point waste difference between high and low accuracy periods, when scaled to commercial operations, represents substantial economic impact. For a 100,000-bird annual operation, this difference equates to approximately 7,600kg of feed saved, valued at $3,420 annually at current feed prices.

Mechanisms of Feed Waste Reduction and Quality Preservation

Feed waste in broiler production arises from multiple mechanisms, each addressed differentially by smart feeding technology. Physical spillage accounted for 42% of total waste in CF group, occurring primarily during aggressive feeding behavior at scheduled meal times when large quantities of fresh feed triggered competitive rushing. Birds displaced feed from feeders through scratching, bill sweeping, and head tossing behaviors, with spillage rates highest during the first 30 minutes following feed delivery when competition intensity peaked. The SF system reduced physical spillage by 67% through three mechanisms: smaller frequent portions reduced competition intensity at each feeding event, continuous feed availability eliminated scheduled meal rush behavior, and feeder sensors detected unusually rapid feed level decreases (indicating spillage) triggering immediate portion size reduction.

Feed quality degradation represented the second major waste category, accounting for 35% of CF group waste. Broiler feed exposed to high temperature (>28°C) and humidity (>70%) conditions for extended periods undergoes oxidative rancidity, moisture absorption, and microbial proliferation, all reducing palatability and nutritional value. In CF system, feed remained in feeders average 8.3 hours between consumptions, with some feed persisting 12+ hours overnight. Palatability testing showed that broilers preferentially consumed fresh feed when both fresh and 8-hour-old feed were simultaneously available, consuming 73% of intake from fresh sources despite equal availability. The SF system maintained average feed age of 2.1 hours through frequent small dispensing, virtually eliminating quality-related refusal. Feed freshness scores (based on moisture content, peroxide value, and palatability indices) averaged 9.1/10 for SF versus 6.8/10 for CF, confirming the quality preservation advantage.

Overfeeding during low-demand periods contributed 23% of CF group waste. Conventional systems dispense predetermined quantities regardless of instantaneous flock requirements, leading to excess feed provision during periods of naturally low consumption (typically midday during heat stress, and overnight when birds rest). This excess feed accumulated in feeders, degraded in quality, and was subsequently refused by birds when their appetite recovered. The IoT system's real-time adjustment capability eliminated this waste source by matching supply precisely to dynamic demand. During heat stress episodes, the system automatically reduced portion sizes during peak temperature hours while proportionally increasing evening and morning portions, maintaining total daily intake while preventing midday waste accumulation.

Detailed Economic Analysis and Break-Even Considerations

The third research objective addressed economic viability through comprehensive cost-benefit analysis. While Table 4 presented basic economic comparison, deeper examination reveals nuanced factors influencing adoption decisions across different operational scales and market contexts. Break-even analysis indicates that minimum flock size for economically justified IoT system adoption is approximately 400 birds per cycle, below which fixed costs per bird become prohibitive. At 400-bird scale, system cost per bird per cycle is $0.42 (assuming $4,800 system cost amortized over 5 years, 6 cycles annually). This cost is recovered through combined savings in feed ($0.22/bird), labor ($0.15/bird), and mortality reduction ($0.08/bird), yielding net benefit of $0.03/bird even at minimum viable scale.

Table 8. Economic analysis by operational scale and sensitivity to key variables

Flock Size	System Cost/Bird/Cycle	Net Benefit/Bird	ROI Period (months)	NPV @ 10% (5 years)
400 birds	$0.42	$0.03	18.5	$856
1,000 birds	$0.17	$0.28	11.0	$6,840
2,500 birds	$0.07	$0.38	7.8	$19,250
5,000 birds	$0.04	$0.41	6.2	$41,500
10,000 birds	$0.02	$0.43	5.1	$86,800
50,000 birds	$0.004	$0.45	3.8	$450,000

Table 8 demonstrates strong positive scale economies in smart feeding adoption. At 10,000-bird operations—typical of mid-sized commercial farms—system cost drops to $0.02/bird while net benefits reach $0.43/bird, yielding ROI period of just 5.1 months and impressive 5-year NPV of $86,800 at 10% discount rate. Large integrators operating 50,000-bird facilities realize even more dramatic benefits, with negligible per-bird system cost ($0.004) and maximum net benefit ($0.45/bird). At this scale, initial investment is recovered in 3.8 months, and 5-year NPV approaches $450,000, strongly justifying technology adoption. These calculations assume current feed prices ($0.45/kg) and market prices ($1.95/kg live weight); sensitivity analysis examined how changing these variables impacts economic viability.

Feed price sensitivity analysis revealed that smart feeding economic advantage strengthens as feed costs increase. At $0.35/kg feed cost (22% below baseline), ROI period extends to 14.2 months for 1,000-bird operations, still acceptable but less compelling. At $0.55/kg (22% above baseline), ROI period contracts to 8.8 months as feed savings increase proportionally. This relationship implies that smart feeding becomes increasingly attractive during periods of high feed prices—precisely when producers most need cost control tools. Similarly, sensitivity to broiler market prices showed asymmetric effects: declining market prices (-20% to $1.56/kg) extended ROI to 13.7 months but still yielded positive returns, while rising prices (-20% to $2.34/kg) accelerated ROI to 8.9 months through higher revenue from improved growth performance.

Labor cost reductions warrant special attention as they represent tangible operational improvements beyond feed savings. The CF system required 52 hours of labor weekly per 1,000 birds for manual feeding operations (feed preparation, distribution, feeder monitoring, record keeping). The SF system reduced this to 31 hours weekly, saving 21 hours valued at $245 per cycle assuming $11.67/hour labor cost (Indonesian agricultural wage). This 40% labor reduction enables either workforce reallocation to other productive activities or reduction in total labor requirements. Larger operations realize proportionally greater absolute labor savings: a 10,000-bird operation saves 210 hours per cycle, equivalent to 1.3 full-time workers. Beyond direct cost savings, labor reduction addresses workforce scarcity challenges increasingly common in many production regions as rural-urban migration reduces agricultural labor availability.

Comparative Performance Against Industry Benchmarks and Standards

Contextualizing study results within broader industry performance standards provides important perspective on practical significance. Ross 308 breed standards specify target FCR of 1.47 at 35 days (2.2kg body weight) under optimal management conditions. The SF system achieved FCR of 1.52, representing 97% of breed genetic potential despite field conditions that inevitably introduce variability absent in breeder trials. This achievement is remarkable considering that average commercial operations typically realize only 85-90% of breed potential due to sub-optimal management, environmental challenges, and disease pressure. The CF group's FCR of 1.78 represents 83% of genetic potential, consistent with conventional commercial performance but confirming substantial room for improvement through enhanced management technologies.

Global broiler production data compiled from FAO statistics and industry reports provide additional comparative context. Average FCR in developed countries ranges from 1.65-1.75, while developing countries typically achieve 1.80-2.00, with the CF group falling near the better end of developing country performance (1.78) and SF group approaching developed country standards (1.52). This comparison suggests smart feeding technology offers developing country producers a pathway to match or exceed developed country performance metrics, potentially enabling market access to premium export channels requiring documented production efficiency. Furthermore, the technology may help narrow the persistent productivity gap between small-holder and industrial operations, as precision feeding benefits scale favorably even to moderate-sized farms (Table 8).

Mortality rates provide another benchmark dimension. The SF group's 2.9% mortality represents best-in-class performance, comparing favorably to industry average of 4-5% in commercial operations and breed standard target of 3.0%. The CF group's 4.6% mortality, while within normal commercial range, demonstrates that conventional management leaves meaningful improvement opportunity. Mortality reduction delivers economic value through both saved input costs (feed, chicks, utilities invested in birds that died) and improved bird welfare. Each percentage point mortality reduction at 1,000-bird scale represents $75 in saved costs, meaning the 1.7 percentage point improvement in SF group generated $128 in mortality-related savings per cycle beyond the direct feed and labor savings previously discussed. At scale, these savings compound significantly: a 50,000-bird operation would save $6,375 per cycle solely from mortality reduction, contributing substantially to overall economic benefits.

Integration with Complementary Technologies and Future Potential

While this study evaluated smart feeding as an isolated intervention, maximum benefits likely emerge from integrated precision livestock farming systems combining multiple technologies. Computer vision systems for individual bird monitoring, automated weighing platforms, advanced environmental controls, and health monitoring sensors could synergistically enhance feeding optimization. For example, integrating thermal imaging cameras could enable the system to detect early disease signs (fever indicated by elevated body temperature) days before clinical symptoms appear, triggering prophylactic feeding adjustments or targeted interventions for affected individuals. Similarly, automated weighing data could refine feeding algorithms by incorporating actual weight trajectories rather than predicted weights, potentially improving prediction accuracy beyond the 5.8% MAPE achieved in this study.

Blockchain integration represents another promising development direction, enabling complete production traceability from feed dispensing through processing and retail sale. Consumers increasingly demand transparency regarding food production practices, particularly concerning animal welfare and environmental sustainability. Blockchain-enabled traceability systems could document precision feeding practices, create verifiable sustainability credentials, and potentially command premium pricing for products demonstrating superior production standards. Preliminary market research suggests consumers in developed countries show 8-12% willingness-to-pay premiums for poultry products with documented welfare and sustainability certifications, potentially adding significant value beyond the direct production efficiency gains demonstrated in this study. Integration with these complementary technologies and market-facing applications represents a frontier for future research and commercial development.

Practical Considerations and Limitations

While results demonstrate substantial benefits, several practical considerations merit discussion. Initial capital investment remains a significant barrier, particularly for small-scale operations. Infrastructure requirements include reliable electrical power and internet connectivity. Farm personnel required approximately one week of training. This study focused on Ross 308 broilers under controlled conditions; performance in alternative genetic lines or housing systems requires validation. Longer-term studies across multiple cycles and seasons would provide valuable information about sustained performance. Integration with other smart farm technologies could yield synergistic benefits not captured in this isolated feeding system evaluation (Menendez et al., 2022; Sztandarski et al., 2025).

The integration of modern technologies with traditional broiler production practices represents a paradigm shift toward data-driven decision-making and precision management. (Brassó et al., 2025) conducted a comprehensive review demonstrating that artificial intelligence and smart technologies substantially enhance poultry productivity through improved monitoring accuracy, predictive disease detection, and optimized environmental control. Their findings emphasized that machine learning algorithms, particularly convolutional neural networks for computer vision applications and deep learning models for behavioral analysis, enable early identification of health problems and stress indicators that remain undetectable through conventional visual inspection methods. These technological capabilities align closely with our findings that IoT-based smart feeding systems achieve significant mortality reduction (2.9% versus 4.6% in conventional systems) through enhanced monitoring and rapid response to consumption anomalies, suggesting that integrated sensor systems provide complementary benefits beyond direct feeding optimization.

The application of machine learning algorithms for feed conversion ratio prediction has emerged as a critical component of precision livestock farming systems. Recent research by (Yang et al., 2025) demonstrated that Gradient Boosting machine learning models achieve remarkable accuracy in predicting long-term FCR using short-term feeding data, with coefficient of determination (R^2) values reaching 0.81 and correlation coefficients of 0.90 when properly calibrated with adequate training data. Their study, utilizing 438,552 feed samples, validated that machine learning algorithms including Random Forest, LightGBM, and CatBoost provide robust data support for precision feeding strategies by accurately forecasting feed efficiency trajectories based on early-life performance indicators. Our implementation of Random Forest algorithms for feed demand prediction achieved comparable performance with Mean Absolute Percentage Error of 5.8%, confirming that properly trained machine learning models can successfully translate real-time sensor data into actionable feeding decisions that significantly improve FCR and reduce feed waste in commercial broiler operations.

The economic and environmental dimensions of digital agricultural technologies in livestock production have gained increasing attention as sustainability pressures intensify globally. (Papadopoulos et al., 2025) systematically reviewed economic and environmental benefits of digital agricultural technological solutions across livestock sectors, demonstrating that precision feeding technologies achieve feed waste reductions up to 75% while generating feeding cost savings of 33%, with automated systems simultaneously reducing labor requirements by 30-45% and greenhouse gas emission intensity by up to 5.83%. Their meta-analysis of 52 peer-reviewed studies confirmed that digital technologies contribute substantially to both economic viability and environmental sustainability through improved resource utilization efficiency and reduced environmental footprint per unit of product. Our findings corroborate these conclusions, with smart feeding achieving 23.9% feed waste reduction, 36.4% labor cost decrease, and 18.7% reduction in production cost per kilogram live weight, suggesting that IoT-based precision feeding systems deliver economic returns that justify capital investment while simultaneously addressing sustainability imperatives through enhanced resource efficiency and reduced environmental impact.

CONCLUSION

This study demonstrates that IoT-based smart feeding systems significantly improve broiler production performance across multiple parameters. The system achieved 14.6% improvement in feed conversion ratio, 14.3% increase in average daily gain, and 23.9% reduction in feed waste compared to conventional feeding methods. These biological improvements translated to substantial economic benefits, with production costs reduced by 18.7% per kilogram live weight and net profit increased by 437% per production cycle. The system demonstrated excellent technical reliability with 99.4% uptime and 94.2% prediction accuracy, validating the feasibility of IoT applications in commercial poultry production environments. The integration of IoT-based smart farming with data analytics represents a convergence of technologies that is reshaping agricultural productivity globally. Recent research on AI-driven forecasting models in agriculture demonstrated that combining IoT sensors with machine learning algorithms enables real-time monitoring of growth conditions, resource allocation optimization, and market dynamics analysis, substantially enhancing both decision-making quality and sustainability outcomes (Elbasi et al., 2023; Javaid et al., 2023).These findings corroborate the 36.4% labor cost reduction and improved feed efficiency observed in our broiler feeding system. Furthermore, the research highlighted that the global smart agriculture market—encompassing precision livestock and crop management—is projected to grow at compound annual rates exceeding 12% through 2031, driven by increasing demand for sustainable intensification, climate adaptation strategies, and food security enhancement in the context of resource scarcity and population growth.

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